

An Enhanced Method For Evaluating Automatic Video Summaries

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Abstract: Evaluation of automatic video summaries is a challenging problem. In the past years, some evaluation methods are presented that utilize only a single feature like color feature to detect similarity between automatic video summaries and ground-truth user summaries. One of the drawbacks of using a single feature is that sometimes it gives a false similarity detection which makes the assessment of the quality of the generated video summary less perceptual and not accurate. In this paper, a novel method for evaluating automatic video summaries is presented. This method is based on comparing automatic video summaries generated by video summarization techniques with ground-truth user summaries. The objective of this evaluation method is to quantify the quality of video summaries, and allow comparing different video summarization techniques utilizing both color and texture features of the video frames and using the Bhattacharya distance as a dissimilarity measure due to its advantages. Our Experiments show that the proposed evaluation method overcomes the drawbacks of other methods and gives a more perceptual evaluation of the quality of the automatic video summaries.

1 INTRODUCTION

A video summary is defined as a sequence of static pictures that represent the content of a video in such a way that the respective target group is rapidly provided with concise information about the content, while the essential message of the original video is preserved (Pfeiffer et al., 1996). Nowadays, a huge amount of digital videos exist in our world and most of them are accessible online like on YouTube. This revolution in digital video has brought new applications and as a consequence research into new technologies to improve the efficiency of video archiving, indexing, and usability of the stored videos. This leads to the requirement of efficient management of video data such as video summarization.

Over the past years, many video summarization techniques have been proposed (de Avila et al., 2011; Furini et al., 2010; Mundur et al., 2006; Sugano et al., 2002; Mahmoud et al., 2013a). However, the task of evaluating the automatic video summaries is still challenging and there is a lack of an efficient evaluation method. In (de Avila et al., 2011), an evaluation method called Comparison of User Summaries (CUS) is used to evaluate the quality of video summaries. In CUS method, the video summary is built manually by a number of users from the sampled frames and the user summaries are taken as reference (i.e. ground

truth) to be compared with the automatic summaries generated by different methods using the Euclidean distance to measure the color similarity between the compared video frames (de Avila et al., 2011).

Although using the color feature to detect similarity between images is efficient in some cases, but it is not sufficient as it may fail in other cases. In this paper, we propose an advanced method to evaluate automatic video summaries. In this method, detecting similar video frames incorporates both color and texture features using the Bhattacharya distance (Kailath, 1967) to measure the similarity between frames. Our Experiments show that utilizing both color and texture features gives a more perceptual assessment of the quality of the video summaries than using a color feature only.

The rest of this paper is organized as follows. Next section presents the proposed evaluation method and shows how to apply it to evaluate automatic video summaries. In section 3, the evaluation metrics used in this method are illustrated. Finally, the experiments and analysis are illustrated in the last section.

2 Proposed Evaluation Method

Figure 1 shows the flowchart of the proposed evaluation method. In this method, the frames in the automatic video summary dataset are compared to the frames in the user summary dataset as follows. First, each frame in the automatic summary is checked to find out if it is color-based matched with one of those frames in the user summary. If the color is matched, both frames in automatic video summary and user summary are counted as matched and the frame in user summary is removed from the user summary list. In case they are not color-based matched, the two frames are checked to find out if they are texture-based matched. If they are found to be texture-based matched, both frames are counted as matched and the frame in user summary is removed from the user summary list. This process continues until automatic video summary frames or user summary frames are processed.

The evaluation process is applied on automatic video summary and correspondent user summary. The detection of similar video frames is done using color or texture features of the compared video frames. Every frame in the automatic summary is compared to the available user summary list. If the two frames are checked to find out if they are matched in color. If they are color-based matched, the next step checks whether they are texture-based matched or not. The two compared frames are considered matched or similar to each other if they are both color-based matched and texture-based matched, in this case the number of the

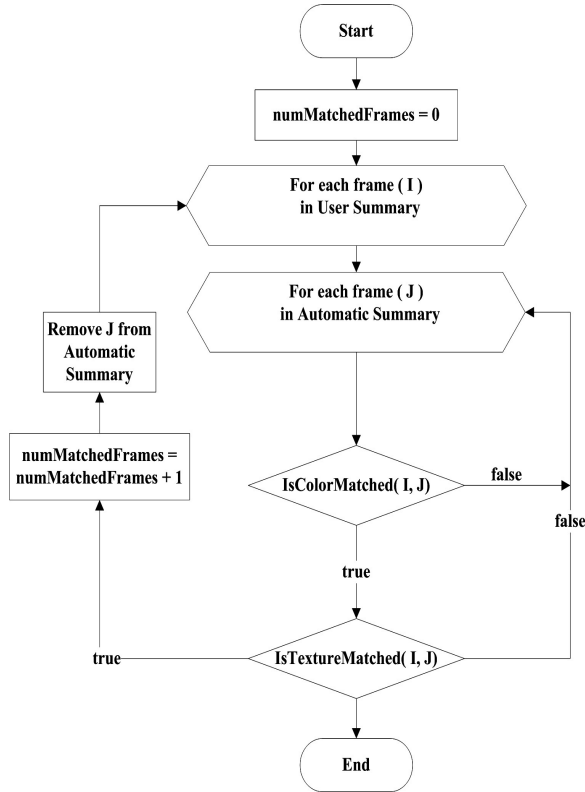


Figure 1: Flowchart of the Proposed Evaluation Method

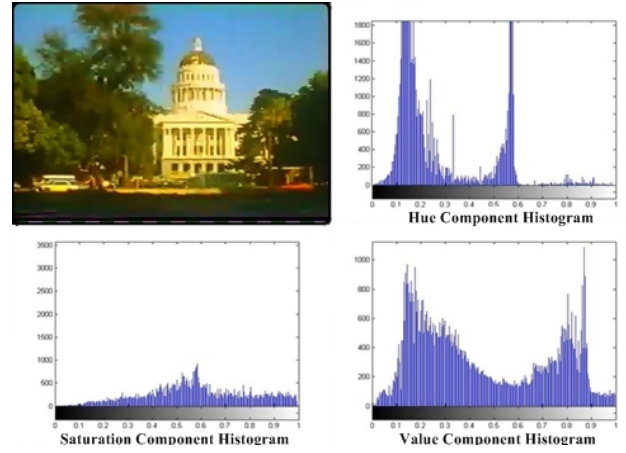


Figure 2: Example of Color Histogram Extracted From a Sample Image

matched frames is incremented and the matched frames are removed from the list. In case if the two compared frames are not matched using color or texture, the process continues to work on the rest of the frames.

The two functions (IsColorMatched) and (IsTextureMatched) shown in the flowchart in figure 1, are used to detect the similarity between the two compared frames using the extracted color and texture features respectively. Next subsections show the details and techniques used to check if there is a matching between the compared video frames using color and texture.

2.1 Color-based Matching

The first step in the comparison procedure is to determine if the compared frames are color-based matched or not. In other words, an efficient technique is needed to detect the similarity of the compared frames based on the extracted color features. In this paper, the color histogram (Swain and Ballard, 1991) is used to extract the color features of frames as it can efficiently describe the visual content. The advantage of using color histogram is that it is invariant to translation and rotation about the viewing axis, and change only slowly under change of angle of view, and change in scale (Manjunath et al., 2001).

Given a discrete color space defined by some color space, the color histogram is obtained by discretizing the image colors and counting the number of times each discrete color occurs in the image array. The color space selected for histogram extraction should reflect the way in which humans perceive color. This can be achieved by using user-oriented color spaces as they employ the characteristics used by humans to distinguish one color from another (Stehling et al., 2002; de Avila et al., 2011). In this paper, the color histogram is extracted from the HSV(Hue-Saturation-Value) color space, as HSV color space was developed to provide an efficient representation of color and to be similar to the way in which humans perceive color (de Avila et al., 2011; Mahmoud et al., 2013a). Figure 2 shows color histogram extracted from a sample image.

The color histogram used in the proposed evaluation

method is computed from the HSV color space using 32 bins of H, 4 bins of S, and 2 bins of V. This quantization of the color histogram is established through experimental tests and aims at reducing the amount of data without losing important information.

After extracting the color features of the compared video frames as mentioned above, and in order to determine if the compared frames are color-based matched or not, the Bhattacharyya distance (Kailath, 1967) between them is calculated, if the distance is greater than threshold value of 0.97 (established through experimental tests), the two compared frames are considered color-based matched.

In this proposed evaluation method, the similarity between the features (color or texture) of the compared frames is measured using the Bhattacharyya distance (Kailath, 1967). The Bhattacharyya distance between two discrete distributions P and Q of size n; is defined as:

$$BhattacharyyaDistance = \sum_{i=0}^n \sqrt{\sum P_i \bullet \sum Q_i} \quad (1)$$

Using the Bhattacharyya distance as dissimilarity measure has many advantages (Aherne et al., 1998). First, the Bhattacharyya measure has self-consistency Property as all poisson errors are forced to be constant therefore ensuring the minimum distance between two observations points is indeed a straight line. Second advantage is the independency between Bhattacharyya measure and bin widths, as the Bhattacharyya metric the contribution to the measure is the same irrespective of how the quantities are divided between bins. Therefore the Bhattacharyya statistic is unaffected by the distribution of data across the histogram and is the only form of sum-of-product functions with this property. Finally, the Bhattacharyya measure is dimensionless, as it is not affected by the measurement scale used, when Bhattacharyya measure is used to compare two identical distributions, it has been proven that the term is maximized to a value of one (Aherne et al., 1998).

2.2 Texture-based Matching

Texture is a powerful low-level feature for the representation of the images. It is defined as an attribute representing the spatial arrangement of the pixels in a region or image (IEE, 1990). Discrete Wavelet Transformation (DWT) is commonly used to extract texture features of an image by transforming it from spatial domain into frequency domain [12]. Wavelet transforms extract information from signal at different scales by passing the signal through low pass and high pass filters. Also, Wavelets provide multi-resolution capability and good energy compaction. In addition, they are robust with respect to color intensity shifts and can capture both texture and shape information efficiently (Singha and Hemachandran, 2012).

In this paper, texture features are extracted using Discrete Haar Wavelet Transforms (Liu et al., 2004), because it is fast to compute and also have been found to perform well in practice. In the proposed evaluation method, to extract the texture features of the compared video frames, first, the frame image is converted into HSV color space. Then, the size of the video frame is reduced into 64 X 64 pixels to reduce the computation. Then, two-dimensional Haar Wavelet transforms on the reduced HSV image data

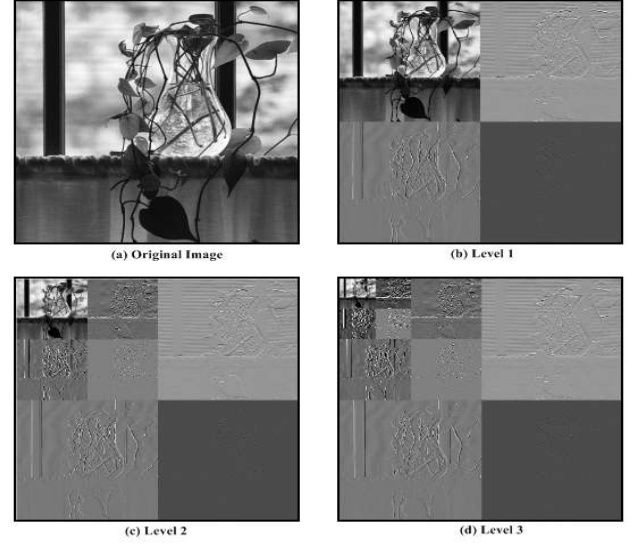


Figure 3: Example of a Haar Wavelet Transformed Image with decomposition level 3

with decomposition level 3. Finally, the texture features are extracted from the approximation coefficients of the Haar Wavelet Transforms. To check if the two compared frames are matched, the Bhattacharyya distance between the texture features is calculated. If the distance is greater than threshold value of 0.97 (value established through experimental tests), the two compared frames are considered texture-based matched. Figure 3 shows an example of a Haar Wavelet Transformed Image with decomposition level 3.

3 Evaluation Metrics

In our proposed evaluation method, the F-measure is used to assess the quality of the automatic summaries. The F-measure combines both Precision and Recall into a single measure by a harmonic mean (Blanken et al., 2007). Precision is defined as the ratio of the number of matched frames (color and texture) to the total number of frames in the automatic summary. Recall is the ratio of the number of matched frames to the total number of frames in the user summary. In simpler terms, high recall means that an algorithm returned most of the relevant results while high precision means that an algorithm returned more relevant results than irrelevant. Following are the equations needed to calculate F-measure.

$$Precision = \frac{\text{Number of matched frames (color and texture)}}{\text{Number of frames in automatic summary}} \quad (2)$$

$$Recall = \frac{\text{Number of matched frames (color and texture)}}{\text{Number of frames in user summary}} \quad (3)$$

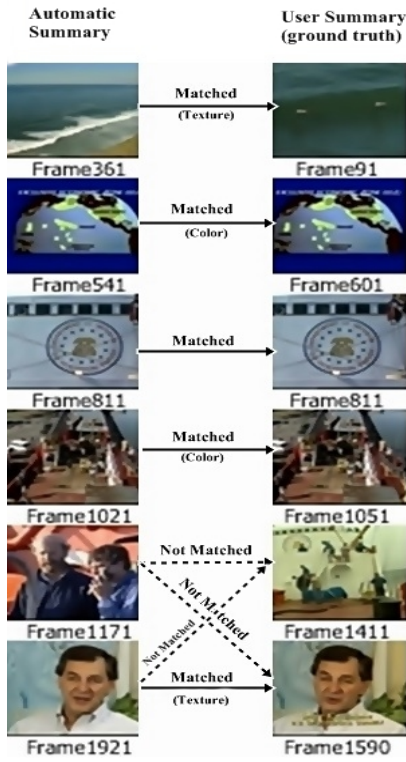


Figure 4: Evaluation of automatic summary of video “America’s New Frontier - segment 05”, available at Open Video Project ¹

$$F\text{-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

4 Experiments and Analysis

In this section, the results of some experiments conducted using the proposed evaluation method are presented. In these experiments, we used a database of 50 videos selected from the Open Video Project ¹. All videos are in MPEG-1 format (30 fps, 352 240 pixels). They are distributed among several genres (documentary, historical, lecture, educational) and their duration varies from 1 to 4 min. Also, we used a user study conducted by (de Avila et al., 2011) as a ground-truth database. In this study, the user summaries were created by 50 users. So, the total number of video summaries created by the users is 250 summaries [10].

The automatic video summaries used in these experiments are generated by the following video summarization approaches: VSCAN (Mahmoud et al., 2013c), VGRAPH (Mahmoud et al., 2013b), VSUMM (de Avila et al., 2011), STIMO (Furini et al., 2010), DT (Mundur et al., 2006), and OV (DeMenthon et al., 1998). The videos used in our exper-

iments, automatic video summaries generated by the previous algorithms.

Table 1: Mean F-measure achieved by different approaches

Video Summarization Method	Mean F-Measure
VSCAN	0.77
VGRAPH	0.75
OV	0.67
DT	0.61
STIMO	0.65
VSUMM	0.72

Table 1 shows the mean F-measure achieved by the different video summarization approaches using our proposed evaluation method. Detailed results for each video sample are available publicly ².

Figure 4 shows the details of applying our proposed evaluation method on video ‘America’s New Frontier - segment 04’, the number of frames in the automatic summary is 8 frames, the number of frames in user summary is 7 frames, and the number of matched frames are 6 frames. The F-measure for this case is calculated as follows: Precision = $\frac{6}{8}$, Recall = $\frac{6}{7}$, so the F-measure = 0.79.

In Figure 4, frame 1921 in automatic summary and frame 1861 in user summary are color-based matched, which have Bhattacharya distance of value 0.973. As a result, if we used the color feature only to evaluate this summary, we will count those frames as matched although they are totally different. To illustrate this point, according to the definition of the color histogram it is obtained by discretizing the image colors and counting the number of times each discrete color occurs in the image array. In Figure 5, if the color histogram is calculated on image 1 and image 2, it will be found identically the same value; while both images are totally different. Also, if the color histogram is calculated on image 3 and image 4, we will find that although the two images are different, the color histogram for both images are equal. According to our experiments, in many cases using the color feature only to detect similarity between compared images was not efficient, as it may give false similarity detection. As a consequence, combining both color and texture features to evaluate video summaries gives a more perceptual assessment of the quality of the automatic video summary.

5 Conclusion

One of the major drawbacks of the currently used video summarization evaluation methods, is that a single feature like: color feature only is used to detect the matching between automatic video summary and user summary. In many cases, this methods gives a false similarity detection which makes the assessment of the quality of the generated video summary less perceptual and not accurate.

¹Open Video Project. <http://www.open-video.org>

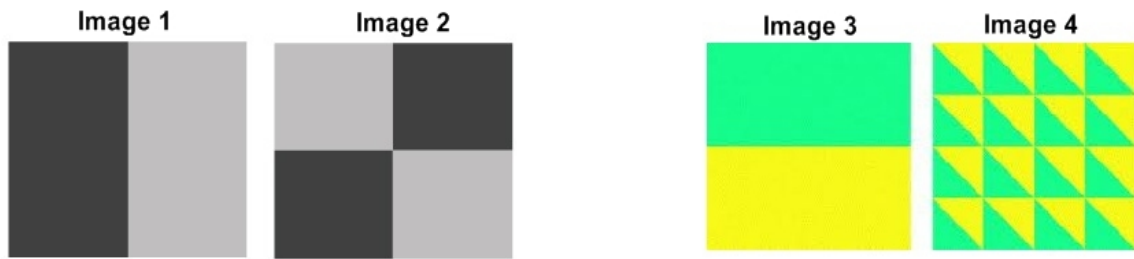


Figure 5: Example of different images having same color histogram. (a) Image 1 and Image 2 are different images having same color histogram. (b) Image 3 and Image 4 are different images having same color histogram

In this paper, a novel method for evaluating automatic video summaries is presented. This method is based on comparing automatic video summaries generated by video summarization techniques with ground-truth user summaries using both color and texture features of the compared video frames. The objective of this evaluation method is to quantify the quality of video summaries more perceptually. Our Experiments show that the proposed evaluation method overcomes the drawbacks of other methods and gives a more perceptual evaluation of the quality of the automatic video summaries.

REFERENCES

- (1990). Ieee standard glossary of image processing and pattern recognition terminology. ieee std 610.4-1990.
- Aherne, F. J., Thacker, N. A., and Rockett, P. I. (1998). The bhattacharyya metric as an absolute similarity measure for frequency coded data. *Kybernetika*, 34(4):363–368.
- Blanken, H. M., De Vries, A., Blok, H. E., and Feng, L. (2007). *Multimedia retrieval*. Springer Verlag.
- de Avila, S. E. F., Lopes, A. P. B., et al. (2011). Vsummm: A mechanism designed to produce static video summaries and a novel evaluation method. *Pattern Recognition Letters*, 32(1):56–68.
- DeMenthon, D., Kobla, V., and Doermann, D. (1998). Video summarization by curve simplification. In *Proceedings of the sixth ACM international conference on Multimedia*, pages 211–218. ACM.
- Furini, M., Geraci, F., Montanero, M., and Pellegrini, M. (2010). Stimo: Still and moving video storyboard for the web scenario. *Multimedia Tools and Applications*, 46(1):47–69.
- Kailath, T. (1967). The divergence and bhattacharyya distance measures in signal selection. *Communication Technology, IEEE Transactions on*, 15(1):52–60.
- Liu, T., Zhang, X., Feng, J., and Lo, K.-T. (2004). Shot reconstruction degree: a novel criterion for key frame selection. *Pattern recognition letters*, 25(12):1451–1457.
- Mahmoud, K. M., Ghanem, N. M., and Ismail, M. A. (2013a). Unsupervised video summarization via dynamic modeling-based hierarchical clustering. In *IEEE International Conference on Machine Learning and Applications-ICMLA 2013*. IEEE.
- Mahmoud, K. M., Ghanem, N. M., and Ismail, M. A. (2013b). VGRAPH: An Effective Approach For Generating Static Video Summaries. In *ICCV Workshops 2013*, pages 811–818. IEEE.
- Mahmoud, K. M., Ismail, M. A., and Ghanem, N. M. (2013c). VSCAN: An Enhanced Video Summarization Using Density-Based Spatial Clustering. In *Image Analysis and Processing Conference-ICIAP 2013*, volume 1, pages 733–742. Springer Berlin Heidelberg.
- Manjunath, B. S., J-R. Ohm, V. V. V., and Yamada, A. (2001). Color and texture descriptors. *Circuits and Systems for Video Technology, IEEE Transactions on*, 11(6):703–715.
- Mundur, P., Rao, Y., and Yesha, Y. (2006). Keyframe-based video summarization using delaunay clustering. *International Journal on Digital Libraries*, 6(2):219–232.
- Pfeiffer, S., Lienhart, R., Fischer, S., and Effelsberg, W. (1996). Abstracting digital movies automatically. *Journal of Visual Communication and Image Representation*, 7(4):345–353.
- Singha, M. and Hemachandran, K. (2012). Signal & image processing: An international journal (sipij). *Content Based Image Retrieval using Color and Texture*, 3 (1), 39-57.
- Stehling, R. O., Nascimento, M. A., and Falcao, A. X. (2002). Techniques for color-based image retrieval. *Multimedia Mining*, pages 61–82.
- Sugano, M., Nakajima, Y., and Yanagihara, H. (2002). Automated mpeg audio-video summarization and description. In *Image Processing. 2002. Proceedings. 2002 International Conference on*, volume 1, pages I-956. IEEE.
- Swain, M. J. and Ballard, D. H. (1991). Color indexing. *International journal of computer vision*, 7(1):11–32.